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APPLICATION NO.	FILING DATE	FIRST NAMED INVENTOR	ATTORNEY DOCKET NO.	CONFIRMATION NO.
09/870,869	05/31/2001	David William Opitz		8976

7590 04/05/2004

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EXAMINER	
BELL, MELTIN	

ART UNIT	PAPER NUMBER
2121	4

DATE MAILED: 04/05/2004

Please find below and/or attached an Office communication concerning this application or proceeding.

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Office Action Summary	Applicati n No.	Applicant(s)	
	09/870,869	OPITZ, DAVID WILLIAM	
	Examiner	Art Unit	
	Meltin Bell	2121	

-- The MAILING DATE of this communication appears on the cover she t with the correspond nce address --

Period for Reply

A SHORTENED STATUTORY PERIOD FOR REPLY IS SET TO EXPIRE 3 MONTH(S) FROM THE MAILING DATE OF THIS COMMUNICATION.

- Extensions of time may be available under the provisions of 37 CFR 1.136(a). In no event, however, may a reply be timely filed after SIX (6) MONTHS from the mailing date of this communication.
- If the period for reply specified above is less than thirty (30) days, a reply within the statutory minimum of thirty (30) days will be considered timely.
- If NO period for reply is specified above, the maximum statutory period will apply and will expire SIX (6) MONTHS from the mailing date of this communication.
- Failure to reply within the set or extended period for reply will, by statute, cause the application to become ABANDONED (35 U.S.C. § 133). Any reply received by the Office later than three months after the mailing date of this communication, even if timely filed, may reduce any earned patent term adjustment. See 37 CFR 1.704(b).

Status

1)☒ Responsive to communication(s) filed on 31 May 2001 and 20 September 2001.

2a)☐ This action is **FINAL**. 2b)☒ This action is non-final.

3)☐ Since this application is in condition for allowance except for formal matters, prosecution as to the merits is closed in accordance with the practice under *Ex parte Quayle*, 1935 C.D. 11, 453 O.G. 213.

Disposition of Claims

4)☒ Claim(s) 1-17 is/are pending in the application.

4a) Of the above claim(s) _____ is/are withdrawn from consideration.

5)☐ Claim(s) _____ is/are allowed.

6)☒ Claim(s) 1-17 is/are rejected.

7)☒ Claim(s) 1-17 is/are objected to.

8)☐ Claim(s) _____ are subject to restriction and/or election requirement.

Application Papers

9)☐ The specification is objected to by the Examiner.

10)☒ The drawing(s) filed on 31 May 2001 is/are: a)☒ accepted or b)☐ objected to by the Examiner.

Applicant may not request that any objection to the drawing(s) be held in abeyance. See 37 CFR 1.85(a).

Replacement drawing sheet(s) including the correction is required if the drawing(s) is objected to. See 37 CFR 1.121(d).

11)☐ The oath or declaration is objected to by the Examiner. Note the attached Office Action or form PTO-152.

Priority under 35 U.S.C. § 119

12)☐ Acknowledgment is made of a claim for foreign priority under 35 U.S.C. § 119(a)-(d) or (f).

a)☐ All b)☐ Some * c)☐ None of:

1.☐ Certified copies of the priority documents have been received.

2.☐ Certified copies of the priority documents have been received in Application No. _____.

3.☐ Copies of the certified copies of the priority documents have been received in this National Stage application from the International Bureau (PCT Rule 17.2(a)).

* See the attached detailed Office action for a list of the certified copies not received.

Attachment(s)

1) ☒ Notice of References Cited (PTO-892)
2) ☐ Notice of Draftsperson's Patent Drawing Review (PTO-948)
3) ☐ Information Disclosure Statement(s) (PTO-1449 or PTO/SB/08) Paper No(s)/Mail Date _____.
4) ☐ Interview Summary (PTO-413) Paper No(s)/Mail Date. _____.
5) ☐ Notice of Informal Patent Application (PTO-152)
6) ☐ Other: _____.

DETAILED ACTION

This action is responsive to application **09/870,869** filed **05/31/01**.

Claims 1-17 have been examined.

Information Disclosure Statement

Applicant is respectfully reminded of the ongoing Duty to disclose 37 C.F.R. 1.56 all pertinent information and material pertaining to the patentability of applicant's claimed invention, by submitting in a timely manner PTO-1449, Information Disclosure Statement (IDS) with the filing of applicant's application or thereafter.

The Invention Background Disclosure signed by the applicant 5/29/01 lists patents (6,212,473; 5,819,247; 5,946,675; 5,222,197; 6,226,627; 5,699,449; 5,201,026; 6,175,643; 5,509,103; 6,035,057) and articles (Drucker; Schapire; Freund; Baner; Breiman; Hansen; Krogh; Maclin; Opitz) in the Duty To Disclose section that are better copied and provided with a PTO-1449.

Drawings

The United States Patent and Trademark Office of Draftsperson's Patent Drawings Review have reviewed the formal drawings. Reasons for any Draftsperson objections under 37 CFR 1.84 or 1.152 will be indicated on the Form PTO-948, Notice of Draftsperson's Patent Drawing Review, if attached.

Specification

The specification has not been checked to the extent necessary to determine the presence of all possible minor errors. Applicant's cooperation is required in correcting any errors of which applicant may become aware in the specification.

Claim Objections

Claim 1-17 are objected to because of the following informalities:

Regarding claim 1:

- 'method for generating ... comprising' would read better as 'computer-implemented method for generating ... comprising the steps of'

Regarding claim 2:

- 'method for generating ... comprising' would read better as 'computer-implemented method for generating ... comprising the step of'

Regarding claim 3:

- 'method for generating ... comprising' would read better as 'computer-implemented method for generating ... comprising the step of'

Regarding claim 4:

- 'method for generating ... comprising' would read better as 'computer-implemented method for generating ... comprising the step of'

Regarding claim 5:

- 'method for generating ... comprising' would read better as 'computer-implemented method for generating ... comprising the step of'

Regarding claim 6:

- 'method for generating ... comprising' would read better as 'computer-implemented method for generating ... comprising the step of'

Regarding claim 7:

- 'method for generating ... comprising' would read better as 'computer-implemented method for generating ... comprising the step of'

Regarding claim 8:

- 'method for generating ... comprising' would read better as 'computer-implemented method for generating ... comprising the step of'

Regarding claim 9:

- 'method for generating ... comprising' would read better as 'computer-implemented method for generating ... comprising the step of'

Regarding claim 10:

- 'method for generating ... comprising' would read better as 'computer-implemented method for generating ... comprising the step of'

Regarding claim 11:

- 'method for generating ... comprising' would read better as 'computer-implemented method for generating ... comprising the step of'

Regarding claim 12:

- 'method for generating ... comprising' would read better as 'computer-implemented method for generating ... comprising the step of'

Regarding claim 13:

- 'method for generating ... comprising' would read better as 'computer-implemented method for generating ... comprising the step of'

Regarding claim 14:

- 'method for generating ... comprising' would read better as 'computer-implemented method for generating ... comprising the step of'

Regarding claim 15:

- 'method for generating ... comprising' would read better as 'computer-implemented method for generating ... comprising the step of'

Regarding claim 16:

- 'method for generating ... comprising' would read better as 'computer-implemented method for generating ... comprising the step of'

Regarding claim 17:

- 'device, for running on a computer,' would read better as 'computer-implemented device'

Claim Rejections - 35 USC § 102

The following is a quotation of the appropriate paragraphs of 35 U.S.C. 102 that form the basis for the rejections under this section made in this Office action:

> A person shall be entitled to a patent unless -
>
> (b) the invention was patented or described in a printed publication in this or a foreign country or in public use or on sale in this country, more than one year prior to the date of application for patent in the United States.

Claims 1-2, 4-5, 7, 10 and 16-17 are rejected under 35 U.S.C. 102(b) as being anticipated by *Becker et al* USPN 5,930,803 (July 27, 1999).

Regarding claim 1:

Becker et al teaches,

- providing a training set of examples to be classified, said training set of examples having an output variable to be predicted containing N target classes (FIGS. 4-11C; column 1, lines 46-48, "Inducers require...the class label"; column 1, lines 55-56, "Once a classifier...of the classes"; column 2, lines 3-11, "A well known...Simple Bayes classifier"; column 23, lines 9-14, "Computer programs...as discussed herein")

- providing a learning means for receiving a subset of said training set of examples and generating an initial hypothesis therefrom, said initial hypothesis predicting a target class for each of said training set of examples (column 1, lines 56-59, "These new records...the label attribute")

- providing a correction means for creating a correction set of examples via a computer-human interface wherein a user validates and corrects the target class of a set of examples beyond said training set of examples, said correction set of examples having an output variable to be predicted containing up to said N target classes (Fig. 15A; column 21, lines 33-52; "The Inducer Options...towards the average")

- providing a retraining means for said learning means to receive a subset of said correction set of examples and a subset of said training set of examples, and generating

a retraining hypothesis therefrom (column 20, lines 22-26, “Cross-validation: The...that holdout fold”)

- providing a refinement means of appending the end of a sequence of hypotheses with said retraining hypothesis creating a resulting sequence of hypotheses, said resulting sequence of hypotheses predicting the target class of each example (column 1, lines 59-62, “if a classifier...predicted iris type”)
- providing a refinement means of replacing the last hypothesis of said sequence of hypotheses with said retraining hypothesis and the resulting sequence of hypotheses predicting the target class of each example (column 19, lines 1-14, “Current Columns window...the previous transformation”)
- repeating the said correction means, said retraining means, and said refinement means process (column 20, lines 27-40, “Cross-validation can be...small data sets”)

Regarding claim 2:

Becker et al teaches,

- said learning means further comprises providing an inductive learning algorithm approach (column 21, lines 19-31, “If the accuracy...Accuracy Options box”)

Regarding claim 4:

Becker et al teaches,

- said learning means further comprises providing a decision tree approach (column 19, lines 27-35, “Alternatively, a Decision-Tree...classifier is realized”)

Regarding claim 5:

The rejection of claim 1 is incorporated. Therefore, claim 5 is rejected under the same rationale as claim 1.

Regarding claim 7:

Becker et al teaches,

- said learning means further comprises providing an instance-based learning approach (column 1, lines 27-32, "Many data mining...more other attributes")

Regarding claim 10:

The rejection of claim 1 is incorporated. Therefore, claim 10 is rejected under the same rationale as claim 1.

Regarding claim 16:

The rejection of claim 1 is incorporated. Therefore, claim 16 is rejected under the same rationale as claim 1.

Regarding claim 17:

Becker et al teaches,

- an input means for receiving a training set of examples, said training set of examples having an output variable to be predicted containing N target classes (FIGS. 4-11C; column 1, lines 46-48, "Inducers require...the class label"; column 1, lines 55-56, "Once a classifier...of the classes"; column 2, lines 3-11, "A well known...Simple Bayes classifier"; column 23, lines 9-14, "Computer programs...as discussed herein")

- a learning means for receiving a subset of said training set of examples and generating an initial hypothesis therefrom, said initial hypothesis predicting a target

class for each of said training set examples (column 1, lines 56-59, "These new records...the label attribute")

- a correction means for creating a correction set of examples via a computer-human interface wherein a user validates and corrects the predicted target class of a set of examples beyond said training set of examples, said correction set of examples having an output variable to be predicted containing up to said N target classes (Fig. 15A; column 21, lines 33-52; "The Inducer Options...towards the average")

- a retraining means for said learning means to receive a subset of said correction set of examples and a subset of said training set of examples, and generating a retraining hypothesis therefrom (column 20, lines 22-26, "Cross-validation: The...that holdout fold")

- a refinement means of appending the end of a sequence of hypotheses with said retraining hypothesis creating a resulting sequence of hypotheses, said resulting sequence of hypotheses predicting the target class of each example (column 1, lines 59-62, "if a classifier...predicted iris type")

- a refinement means of replacing the last hypothesis of said sequence of hypotheses with said retraining hypothesis and the resulting sequence of hypotheses predicting the target class of each example (column 19, lines 1-14, "Current Columns window...the previous transformation")

- a repeating means, for repeating the said correction means, said retraining means, and said refinement means process (column 20, lines 27-40, "Cross-validation can be...small data sets")

Claim Rejections - 35 USC § 103

The following is a quotation of 35 U.S.C. 103(a) which forms the basis for all obviousness rejections set forth in this Office action:

> (a) A patent may not be obtained though the invention is not identically disclosed or described as set forth in section 102 of this title, if the differences between the subject matter sought to be patented and the prior art are such that the subject matter as a whole would have been obvious at the time the invention was made to a person having ordinary skill in the art to which said subject matter pertains. Patentability shall not be negatived by the manner in which the invention was made.

Claim 3, 6, 8-9 and 11-15 are rejected under 35 U.S.C. 103(a) as being unpatentable over *Becker et al* USPN 5,930,803 (July 27, 1999) in view of

- *Gevins et al* USPN 4,736,751 (April 12, 1988) in further view of
- *Connell et al* USPN 5,649,070 (July 15, 1997) in further view of
- *Katic et al* "Highly efficient robot dynamics learning by decomposed connectionist feedforward control structure" (September 23, 1997) in further view of
- *Benitz et al* USPN 6,067,638 (May 23, 2000) in further view of
- *Georgilakis et al* "A Neural Network Framework for Predicting Transformer Core Losses" (July 1999) in further view of
- *Parekh et al* "Constructive theory refinement in knowledge based neural networks" (4-9 May 1998)

and further in view of *Mangasarian et al* "Successive Overrelaxation for Support Vector Machines" (September 1999).

Regarding claim 3:

Becker et al teaches,

- providing a training set of examples to be classified, said training set of examples having an output variable to be predicted containing N target classes (FIGS. 4-11C; column 1, lines 46-48, "Inducers require...the class label"; column 1, lines 55-56, "Once a classifier...of the classes"; column 2, lines 3-11, "A well known...Simple Bayes classifier"; column 23, lines 9-14, "Computer programs...as discussed herein")
- providing a learning means for receiving a subset of said training set of examples and generating an initial hypothesis therefrom, said initial hypothesis predicting a target class for each of said training set of examples (column 1, lines 56-59, "These new records...the label attribute")
- providing a correction means for creating a correction set of examples via a computer-human interface wherein a user validates and corrects the target class of a set of examples beyond said training set of examples, said correction set of examples having an output variable to be predicted containing up to said N target classes (Fig. 15A; column 21, lines 33-52; "The Inducer Options...towards the average")
- providing a retraining means for said learning means to receive a subset of said correction set of examples and a subset of said training set of examples, and generating a retraining hypothesis therefrom (column 20, lines 22-26, "Cross-validation: The...that holdout fold")
- providing a refinement means of appending the end of a sequence of hypotheses with said retraining hypothesis creating a resulting sequence of hypotheses, said resulting

sequence of hypotheses predicting the target class of each example (column 1, lines 59-62, "if a classifier...predicted iris type")

- providing a refinement means of replacing the last hypothesis of said sequence of hypotheses with said retraining hypothesis and the resulting sequence of hypotheses predicting the target class of each example (column 19, lines 1-14, "Current Columns window...the previous transformation")
- repeating the said correction means, said retraining means, and said refinement means process (column 20, lines 27-40, "Cross-validation can be...small data sets")

However, *Becker et al* doesn't explicitly teach neural networks while *Georgilakis et al* teaches,

- said learning means further comprises providing a neural network approach (Title, "A Neural Network ... Transformer Core Losses")

Motivation - The portions of the claimed method would have been a highly desirable feature in this art for

- Increasing prediction accuracy (*Georgilakis et al*, Abstract, "In this paper...the current practice")
- Filtering low count attribute values (*Becker et al*, column 4, lines 62-67, "a count slider...the count slider")

Therefore, it would have been obvious to one of ordinary skill in the art at the time the invention was made to combine *Becker et al* with *Georgilakis et al* to obtain the invention specified in claim 3, a method for generating a sequence of hypotheses. The

modification would have been obvious because one of ordinary skill in the art would have been motivated to accurately predict relevant attributes.

Regarding claim 6:

Becker et al teaches,

- providing a training set of examples to be classified, said training set of examples having an output variable to be predicted containing N target classes (FIGS. 4-11C; column 1, lines 46-48, "Inducers require...the class label"; column 1, lines 55-56, "Once a classifier...of the classes"; column 2, lines 3-11, "A well known...Simple Bayes classifier"; column 23, lines 9-14, "Computer programs...as discussed herein")
- providing a learning means for receiving a subset of said training set of examples and generating an initial hypothesis therefrom, said initial hypothesis predicting a target class for each of said training set of examples (column 1, lines 56-59, "These new records...the label attribute")
- providing a correction means for creating a correction set of examples via a computer-human interface wherein a user validates and corrects the target class of a set of examples beyond said training set of examples, said correction set of examples having an output variable to be predicted containing up to said N target classes (Fig. 15A; column 21, lines 33-52; "The Inducer Options...towards the average")
- providing a retraining means for said learning means to receive a subset of said correction set of examples and a subset of said training set of examples, and generating a retraining hypothesis therefrom (column 20, lines 22-26, "Cross-validation: The...that holdout fold")

- providing a refinement means of appending the end of a sequence of hypotheses with said retraining hypothesis creating a resulting sequence of hypotheses, said resulting sequence of hypotheses predicting the target class of each example (column 1, lines 59-62, "if a classifier...predicted iris type")
- providing a refinement means of replacing the last hypothesis of said sequence of hypotheses with said retraining hypothesis and the resulting sequence of hypotheses predicting the target class of each example (column 19, lines 1-14, "Current Columns window...the previous transformation")
- repeating the said correction means, said retraining means, and said refinement means process (column 20, lines 27-40, "Cross-validation can be...small data sets")

However, *Gevins et al* doesn't explicitly teach linear or nonlinear regression while *Gevins et al* teaches,

- said learning means further comprises providing a linear or nonlinear regression approach (column 16, lines 27-32, "The major advantage ... each candidate source")

Motivation - The portions of the claimed method would have been a highly desirable feature in this art for

- Simplifying computation (*Gevins et al*, column 16, lines 32-45, "The method unambiguously...the computations feasible"; Fig. 12)
- Filtering low count attribute values (*Becker et al*, column 4, lines 62-67, "a count slider...the count slider")

Therefore, it would have been obvious to one of ordinary skill in the art at the time the invention was made to combine *Becker et al* with *Gevins et al* to obtain the invention

specified in claim 6, a method for generating a sequence of hypotheses. The modification would have been obvious because one of ordinary skill in the art would have been motivated to simply predict relevant attributes.

Regarding claim 8:

Becker et al teaches,

- providing a training set of examples to be classified, said training set of examples having an output variable to be predicted containing N target classes (FIGS. 4-11C; column 1, lines 46-48, "Inducers require...the class label"; column 1, lines 55-56, "Once a classifier...of the classes"; column 2, lines 3-11, "A well known...Simple Bayes classifier"; column 23, lines 9-14, "Computer programs...as discussed herein")

- providing a learning means for receiving a subset of said training set of examples and generating an initial hypothesis therefrom, said initial hypothesis predicting a target class for each of said training set of examples (column 1, lines 56-59, "These new records...the label attribute")

- providing a correction means for creating a correction set of examples via a computer-human interface wherein a user validates and corrects the target class of a set of examples beyond said training set of examples, said correction set of examples having an output variable to be predicted containing up to said N target classes (Fig. 15A; column 21, lines 33-52; "The Inducer Options...towards the average")

- providing a retraining means for said learning means to receive a subset of said correction set of examples and a subset of said training set of examples, and generating

a retraining hypothesis therefrom (column 20, lines 22-26, "Cross-validation: The...that holdout fold")

- providing a refinement means of appending the end of a sequence of hypotheses with said retraining hypothesis creating a resulting sequence of hypotheses, said resulting sequence of hypotheses predicting the target class of each example (column 1, lines 59-62, "if a classifier...predicted iris type")
- providing a refinement means of replacing the last hypothesis of said sequence of hypotheses with said retraining hypothesis and the resulting sequence of hypotheses predicting the target class of each example (column 19, lines 1-14, "Current Columns window...the previous transformation")
- repeating the said correction means, said retraining means, and said refinement means process (column 20, lines 27-40, "Cross-validation can be...small data sets")

However, *Becker et al* doesn't explicitly teach nearest neighbor learning while *Connell et al* teaches,

- said learning means further comprises providing a nearest-neighbor learning approach (column 1, lines 12-18, "Learning systems exist...generalized category descriptions")

<u>Motivation</u> - The portions of the claimed method would have been a highly desirable feature in this art for

- Fast recognition (*Connell et al*, column 1, lines 18-21, "These generalized descriptions...accomplishing this recognition")
- Filtering low count attribute values (*Becker et al*, column 4, lines 62-67, "a count slider...the count slider")

Therefore, it would have been obvious to one of ordinary skill in the art at the time the invention was made to combine *Becker et al* with *Connell et al* to obtain the invention specified in claim 8, a method for generating a sequence of hypotheses. The modification would have been obvious because one of ordinary skill in the art would have been motivated to quickly predict relevant attributes.

Regarding claim 9:

Becker et al teaches,

- providing a training set of examples to be classified, said training set of examples having an output variable to be predicted containing N target classes (FIGS. 4-11C; column 1, lines 46-48, "Inducers require...the class label"; column 1, lines 55-56, "Once a classifier...of the classes"; column 2, lines 3-11, "A well known...Simple Bayes classifier"; column 23, lines 9-14, "Computer programs...as discussed herein")

- providing a learning means for receiving a subset of said training set of examples and generating an initial hypothesis therefrom, said initial hypothesis predicting a target class for each of said training set of examples (column 1, lines 56-59, "These new records...the label attribute")

- providing a correction means for creating a correction set of examples via a computer-human interface wherein a user validates and corrects the target class of a set of examples beyond said training set of examples, said correction set of examples having an output variable to be predicted containing up to said N target classes (Fig. 15A; column 21, lines 33-52; "The Inducer Options...towards the average")

- providing a retraining means for said learning means to receive a subset of said correction set of examples and a subset of said training set of examples, and generating a retraining hypothesis therefrom (column 20, lines 22-26, "Cross-validation: The…that holdout fold")
- providing a refinement means of appending the end of a sequence of hypotheses with said retraining hypothesis creating a resulting sequence of hypotheses, said resulting sequence of hypotheses predicting the target class of each example (column 1, lines 59-62, "if a classifier…predicted iris type")
- providing a refinement means of replacing the last hypothesis of said sequence of hypotheses with said retraining hypothesis and the resulting sequence of hypotheses predicting the target class of each example (column 19, lines 1-14, "Current Columns window…the previous transformation")
- repeating the said correction means, said retraining means, and said refinement means process (column 20, lines 27-40, "Cross-validation can be…small data sets")

However, *Becker et al* doesn't explicitly teach connectionist learning while *Katic et al* teaches,

- said learning means further comprises providing a connectionist learning approach (Title, "Highly Efficient Robot … Feedforward Control Structure")

<u>Motivation</u> - The portions of the claimed method would have been a highly desirable feature in this art for

- Fast and robust learning (*Katic et al*, Abstract, "A major objective…back propagation algorithm")

- Filtering low count attribute values (*Becker et al*, column 4, lines 62-67, "a count slider...the count slider")

Therefore, it would have been obvious to one of ordinary skill in the art at the time the invention was made to combine *Becker et al* with *Katic et al* to obtain the invention specified in claim 9, a method for generating a sequence of hypotheses. The modification would have been obvious because one of ordinary skill in the art would have been motivated to quickly predict relevant attributes.

Regarding claim 11:

Becker et al teaches,

- providing a training set of examples to be classified, said training set of examples having an output variable to be predicted containing N target classes (FIGS. 4-11C; column 1, lines 46-48, "Inducers require...the class label"; column 1, lines 55-56, "Once a classifier...of the classes"; column 2, lines 3-11, "A well known...Simple Bayes classifier"; column 23, lines 9-14, "Computer programs...as discussed herein")

- providing a learning means for receiving a subset of said training set of examples and generating an initial hypothesis therefrom, said initial hypothesis predicting a target class for each of said training set of examples (column 1, lines 56-59, "These new records...the label attribute")

- providing a correction means for creating a correction set of examples via a computer-human interface wherein a user validates and corrects the target class of a set of examples beyond said training set of examples, said correction set of examples having

an output variable to be predicted containing up to said N target classes (Fig. 15A; column 21, lines 33-52; "The Inducer Options...towards the average")

- providing a retraining means for said learning means to receive a subset of said correction set of examples and a subset of said training set of examples, and generating a retraining hypothesis therefrom (column 20, lines 22-26, "Cross-validation: The...that holdout fold")
- providing a refinement means of appending the end of a sequence of hypotheses with said retraining hypothesis creating a resulting sequence of hypotheses, said resulting sequence of hypotheses predicting the target class of each example (column 1, lines 59-62, "if a classifier...predicted iris type")
- providing a refinement means of replacing the last hypothesis of said sequence of hypotheses with said retraining hypothesis and the resulting sequence of hypotheses predicting the target class of each example (column 19, lines 1-14, "Current Columns window...the previous transformation")
- repeating the said correction means, said retraining means, and said refinement means process (column 20, lines 27-40, "Cross-validation can be...small data sets")

However, *Becker et al* doesn't explicitly teach a pattern recognizer learning approach while *Gevins et al* teaches,

- said learning means further comprises providing a pattern recognizer learning approach (Fig. 4)

<u>Motivation</u> - The portions of the claimed method would have been a highly desirable feature in this art for

- Simplifying computation (*Gevins et al*, column 16, lines 32-45, "The method unambiguously...the computations feasible"; Fig. 12)
- Filtering low count attribute values (*Becker et al*, column 4, lines 62-67, "a count slider...the count slider")

Therefore, it would have been obvious to one of ordinary skill in the art at the time the invention was made to combine *Becker et al* with *Gevins et al* to obtain the invention specified in claim 11, a method for generating a sequence of hypotheses. The modification would have been obvious because one of ordinary skill in the art would have been motivated to simply predict relevant attributes.

Regarding claim 12:

Becker et al teaches,

- providing a training set of examples to be classified, said training set of examples having an output variable to be predicted containing N target classes (FIGS. 4-11C; column 1, lines 46-48, "Inducers require...the class label"; column 1, lines 55-56, "Once a classifier...of the classes"; column 2, lines 3-11, "A well known... Simple Bayes classifier"; column 23, lines 9-14, "Computer programs...as discussed herein")

- providing a learning means for receiving a subset of said training set of examples and generating an initial hypothesis therefrom, said initial hypothesis predicting a target class for each of said training set of examples (column 1, lines 56-59, "These new records...the label attribute")

- providing a correction means for creating a correction set of examples via a computer-human interface wherein a user validates and corrects the target class of a set of

examples beyond said training set of examples, said correction set of examples having an output variable to be predicted containing up to said N target classes (Fig. 15A; column 21, lines 33-52; "The Inducer Options...towards the average")

- providing a retraining means for said learning means to receive a subset of said correction set of examples and a subset of said training set of examples, and generating a retraining hypothesis therefrom (column 20, lines 22-26, "Cross-validation: The...that holdout fold")
- providing a refinement means of appending the end of a sequence of hypotheses with said retraining hypothesis creating a resulting sequence of hypotheses, said resulting sequence of hypotheses predicting the target class of each example (column 1, lines 59-62, "if a classifier...predicted iris type")
- providing a refinement means of replacing the last hypothesis of said sequence of hypotheses with said retraining hypothesis and the resulting sequence of hypotheses predicting the target class of each example (column 19, lines 1-14, "Current Columns window...the previous transformation")
- repeating the said correction means, said retraining means, and said refinement means process (column 20, lines 27-40, "Cross-validation can be...small data sets")

However, *Becker et al* doesn't explicitly teach reinforcement learning while *Benitz et al* teaches,

- said learning means further comprises providing a reinforcement learning approach (column 12, lines 16-31, "In step 504 ... interactive multimedia application")

Motivation - The portions of the claimed method would have been a highly desirable feature in this art for

- Thoroughness and repeatability in complex interactive applications (*Benitz et al*, column 3, lines 26-27, "What is needed... interactive multimedia applications")
- Filtering low count attribute values (*Becker et al*, column 4, lines 62-67, "a count slider... the count slider")

Therefore, it would have been obvious to one of ordinary skill in the art at the time the invention was made to combine *Becker et al* with *Benitz et al* to obtain the invention specified in claim 12, a method for generating a sequence of hypotheses. The modification would have been obvious because one of ordinary skill in the art would have been motivated to repeatedly predict relevant attributes.

Regarding claim 13:

Becker et al teaches,

- providing a training set of examples to be classified, said training set of examples having an output variable to be predicted containing N target classes (FIGS. 4-11C; column 1, lines 46-48, "Inducers require... the class label"; column 1, lines 55-56, "Once a classifier... of the classes"; column 2, lines 3-11, "A well known... Simple Bayes classifier"; column 23, lines 9-14, "Computer programs... as discussed herein")

- providing a learning means for receiving a subset of said training set of examples and generating an initial hypothesis therefrom, said initial hypothesis predicting a target class for each of said training set of examples (column 1, lines 56-59, "These new records... the label attribute")

- providing a correction means for creating a correction set of examples via a computer-human interface wherein a user validates and corrects the target class of a set of examples beyond said training set of examples, said correction set of examples having an output variable to be predicted containing up to said N target classes (Fig. 15A; column 21, lines 33-52; "The Inducer Options…towards the average")
- providing a retraining means for said learning means to receive a subset of said correction set of examples and a subset of said training set of examples, and generating a retraining hypothesis therefrom (column 20, lines 22-26, "Cross-validation: The…that holdout fold")
- providing a refinement means of appending the end of a sequence of hypotheses with said retraining hypothesis creating a resulting sequence of hypotheses, said resulting sequence of hypotheses predicting the target class of each example (column 1, lines 59-62, "if a classifier…predicted iris type")
- providing a refinement means of replacing the last hypothesis of said sequence of hypotheses with said retraining hypothesis and the resulting sequence of hypotheses predicting the target class of each example (column 19, lines 1-14, "Current Columns window…the previous transformation")
- repeating the said correction means, said retraining means, and said refinement means process (column 20, lines 27-40, "Cross-validation can be…small data sets")

However, *Becker et al* doesn't explicitly teach support vector machine learning while *Mangasarian et al* teaches,

- said learning means further comprises providing a support vector machine learning approach (Title, "Successive Overrelaxation for Support Vector Machines")

Motivation - The portions of the claimed method would have been a highly desirable feature in this art for

- Fast data discrimination (*Mangasarian et al*, Abstract, "Successive overrelaxation (SOR...faster than SMO")
- Filtering low count attribute values (*Becker et al*, column 4, lines 62-67, "a count slider...the count slider")

Therefore, it would have been obvious to one of ordinary skill in the art at the time the invention was made to combine *Becker et al* with *Mangasarian et al* to obtain the invention specified in claim 13, a method for generating a sequence of hypotheses. The modification would have been obvious because one of ordinary skill in the art would have been motivated to quickly predict relevant attributes.

Regarding claim 14:

Becker et al teaches,

- providing a training set of examples to be classified, said training set of examples having an output variable to be predicted containing N target classes (FIGS. 4-11C; column 1, lines 46-48, "Inducers require...the class label"; column 1, lines 55-56, "Once a classifier...of the classes"; column 2, lines 3-11, "A well known...Simple Bayes classifier"; column 23, lines 9-14, "Computer programs...as discussed herein")

- providing a learning means for receiving a subset of said training set of examples and generating an initial hypothesis therefrom, said initial hypothesis predicting a target

class for each of said training set of examples (column 1, lines 56-59, "These new records...the label attribute")

- providing a correction means for creating a correction set of examples via a computer-human interface wherein a user validates and corrects the target class of a set of examples beyond said training set of examples, said correction set of examples having an output variable to be predicted containing up to said N target classes (Fig. 15A; column 21, lines 33-52; "The Inducer Options...towards the average")
- providing a retraining means for said learning means to receive a subset of said correction set of examples and a subset of said training set of examples, and generating a retraining hypothesis therefrom (column 20, lines 22-26, "Cross-validation: The...that holdout fold")
- providing a refinement means of appending the end of a sequence of hypotheses with said retraining hypothesis creating a resulting sequence of hypotheses, said resulting sequence of hypotheses predicting the target class of each example (column 1, lines 59-62, "if a classifier...predicted iris type")
- providing a refinement means of replacing the last hypothesis of said sequence of hypotheses with said retraining hypothesis and the resulting sequence of hypotheses predicting the target class of each example (column 19, lines 1-14, "Current Columns window...the previous transformation")
- repeating the said correction means, said retraining means, and said refinement means process (column 20, lines 27-40, "Cross-validation can be...small data sets")

However, *Becker et al* doesn't explicitly teach ensemble learning while *Gevins et al* teaches,

- said learning means further comprises providing an ensemble learning approach (Fig. 8)

<u>Motivation</u> - The portions of the claimed method would have been a highly desirable feature in this art for

- Simplifying computation (*Gevins et al*, column 16, lines 32-45, "The method unambiguously...the computations feasible"; Fig. 12)
- Filtering low count attribute values (*Becker et al*, column 4, lines 62-67, "a count slider...the count slider")

Therefore, it would have been obvious to one of ordinary skill in the art at the time the invention was made to combine *Becker et al* with *Gevins et al* to obtain the invention specified in claim 14, a method for generating a sequence of hypotheses. The modification would have been obvious because one of ordinary skill in the art would have been motivated to simply predict relevant attributes.

Regarding claim 15:

Becker et al teaches,

- providing a training set of examples to be classified, said training set of examples having an output variable to be predicted containing N target classes (FIGS. 4-11C; column 1, lines 46-48, "Inducers require...the class label"; column 1, lines 55-56, "Once a classifier...of the classes"; column 2, lines 3-11, "A well known...Simple Bayes classifier"; column 23, lines 9-14, "Computer programs...as discussed herein")

- providing a learning means for receiving a subset of said training set of examples and generating an initial hypothesis therefrom, said initial hypothesis predicting a target class for each of said training set of examples (column 1, lines 56-59, "These new records...the label attribute")
- providing a correction means for creating a correction set of examples via a computer-human interface wherein a user validates and corrects the target class of a set of examples beyond said training set of examples, said correction set of examples having an output variable to be predicted containing up to said N target classes (Fig. 15A; column 21, lines 33-52; "The Inducer Options...towards the average")
- providing a retraining means for said learning means to receive a subset of said correction set of examples and a subset of said training set of examples, and generating a retraining hypothesis therefrom (column 20, lines 22-26, "Cross-validation: The...that holdout fold")
- providing a refinement means of appending the end of a sequence of hypotheses with said retraining hypothesis creating a resulting sequence of hypotheses, said resulting sequence of hypotheses predicting the target class of each example (column 1, lines 59-62, "if a classifier...predicted iris type")
- providing a refinement means of replacing the last hypothesis of said sequence of hypotheses with said retraining hypothesis and the resulting sequence of hypotheses predicting the target class of each example (column 19, lines 1-14, "Current Columns window...the previous transformation")

- repeating the said correction means, said retraining means, and said refinement means process (column 20, lines 27-40, "Cross-validation can be...small data sets")

However, *Becker et al* doesn't explicitly teach theory-refinement while *Parekh et al* teaches,

- said learning means further comprises providing a theory-refinement learning approach (Title, "Constructive theory refinement ... based neural networks")

Motivation - The portions of the claimed method would have been a highly desirable feature in this art for

- Superior generalization accuracy (*Parekh et al*, page 2322, right column, paragraph 5, "Experimental results demonstrate...imperfect domain theory")
- Filtering low count attribute values (*Becker et al*, column 4, lines 62-67, "a count slider...the count slider")

Therefore, it would have been obvious to one of ordinary skill in the art at the time the invention was made to combine *Becker et al* with *Parekh et al* to obtain the invention specified in claim 15, a method for generating a sequence of hypotheses. The modification would have been obvious because one of ordinary skill in the art would have been motivated to accurately predict relevant attributes.

Conclusion

The prior art made of record and not relied upon is considered pertinent to applicant's disclosure:

- *Becker et al;* USPN 5,930,803

- *Gevins et al ;* USPN 4,736,751

- *Connell et al;* USPN 5,649,070

- *Benitz et al;* USPN 6,067,638

- *Mangasarian et al;* "Successive Overrelaxation for Support Vector Machines"

- *Georgilakis et al;* "A Neural Network Framework for Predicting Transformer Core Losses"

- *Katic et al;* "Highly efficient robot dynamics learning by decomposed connectionist feedforward control structure"

- *Parekh et al;* "Constructive theory refinement in knowledge based neural networks"

- *Catlett et al;* USPN 5,671,333; Training Apparatus and Method

- *Hakmatpour;* USPN 5,644,686; Expert System and Method Employing Hierarchical Knowledge Base, and Interactive Multimedia/Hypermedia Applications

- *Elghazzawi;* USPN 5,819,007; Feature-Based Expert System Classifier

- *Clark et al;* USPN 5,222,014; Integrated Qualitative/Quantitative Reasoning With Enhanced Core Predictions and Extended Test Procedures for Machine Failure Isolation Using Qualitative Physics

- *Steels;* USPN 6,247,002; Method and Apparatus for Extracting Features Characterizing Objects, and Use Thereof

- *Teng et al;* USPN 5,222,197; Rule Invocation Mechanism for Inductive Learning Engine

- *Freund et al;* USPN 5,819,247; Apparatus and Methods for Machine Learning Hypotheses

- *Gustafson;* USPN 5,659,731; Method for Rating a Match for a Given Entity Found in a List of Entities
- *Tsuiki;* USPN 5,201,026; Method of Architecting Multiple Neural Network and System Therefor
- *Sutton;* USPN 5,946,675; Apparatus for Machine Learning
- *Opitz et al*; "Using neural networks to automatically refine expert system knowledge bases: experiments in the NYNEX MAX domain"; Neural Networks, International Conference on; Vol. 1; 9-12 June 1997; pp 16 - 20
- *Yang et al;* "Data-driven theory refinement algorithms for bioinformatics"; Neural Networks, International Joint Conference on; Vol. 6; 10-16 July 1999; pp 4064 - 4068
- *Opitz et al*; "Popular Ensemble Methods: An Empirical Study"; Journal of Artificial Intelligence Research; Vol. 11; August 1999; pp 169-198
- *Eliassi-Rad et al*; "A Theory-Refinement Approach to Information Extraction"; Proceedings of the 18th International Conference on Machine Learning; 2001

Any inquiry concerning this communication or earlier communications from the Office should be directed to Meltin Bell whose telephone number is 703-305-0362. This Examiner can normally be reached on Mon - Fri 7:30 am - 4:30 pm.

If attempts to reach this Examiner by telephone are unsuccessful, his supervisor, Anil Khatri, can be reached on 703-305-0282. The fax phone number for the organization where this application or proceeding is assigned is (703) 872-9306.

Any inquiry of a general nature or relating to the status of this application or proceeding should be directed to the receptionist whose telephone number is 703-305-3900.

MB /MB/

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